# ReWIRED:
# Instructional Explanations in Teacher-Student Dialogues

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## Abstract

How to assess the quality of teaching in instructional explanation dialogues is a recurring point of debate in didactics research. For the NLP community, this is a challenging topic thus far, even with the use of LLMs. To address the matter, we create a new annotation scheme of teaching acts aligned with contemporary didactic teaching models. On this basis, we extend an existing dataset of conversational explanations about communicating scientific understanding in teacher-student settings on five levels of the explainee's expertise, with the proposed teaching annotation: explanation and dialogue acts. For better granularity, we reframe the task from a dialogue turn classification to a span labeling task. We then evaluate language models on the labeling of such acts and find that the broad range and structure of the proposed labels is hard to model for LLMs such as `GPT-3.5/-4` via prompting, but a fine-tuned `BERT` can perform both act classification and span labeling well. Finally, we operationalize a series of quality metrics for instructional explanations in the form of a test suite. We find that they match the five expertise levels well and that experts in our data often stick to best practices in teaching.



Figure 1: Instructional explanation dialogue of an expert (center) explaining machine learning to a child (left). Labels on the right indicate the teaching act associated with the turn(s) or span(s) with the same color.

## 1 Introduction

The recent paradigm shift in NLP towards LLMs such as ChatGPT has impacted cross-disciplinary research with education and other social sciences. However, automating teacher coaching (Wang and Demszky, 2023) and student tutoring (Macina et al., 2023) has shown limited success so far. A recent work in tutoring by Lee et al. (2023) has explored creating interactive dialogues to answer children's why and how questions. Measures for estimating the quality of discourse (McNamara et al., 2014) or model-generated explanations (Schuff et al., 2023) exist, but it is unclear how we can assess the quality of teaching in such instructional explanation dialogues and also consider the expertise level of the explainee (Wachsmuth and Alshomary, 2022).

In this work, we first propose a scheme of teaching acts that connect dialogical surface-level utterances with the processes described by two popular teaching models (§2). Thereby, we open the doors to the large-scale analysis of teaching strategies, a goal much sought after in didactics (Matsumura et al., 2008). Secondly, we re-annotate the WIRED dataset from Wachsmuth and Alshomary (2022) to include our scheme of teaching acts, expanding on the two act sets from the original, dialogue acts and explanation acts (§3). The dataset is further enhanced by the inclusion of 45 new conversation transcripts, and by a switch from a turn-labeling to a span-labeling setting for higher granularity.

We evaluate state-of-the-art language models of different sizes on both turn classification and span labeling (§4) and find that large closed-source models cannot perform either task reasonably well and is easily beaten by a fine-tuned BERT. Lastly, to measure "good teaching" according to didactics research in terms of both *meaning* and *form* (Bender and Koller, 2020), we implement a series of quality metrics for instructional explanations, taking into account the presence and order of teaching acts as well as frequency of explanatory patterns. We dub this new test suite IXQUISITE (§5.3) and find that the metrics correlate well with the five expertise levels in our dataset.

With the results and findings of this paper, we contribute to both fields, NLP and didactics: To NLP, a more accurate representation of the complex sociolinguistic goals affecting the enactment of effective instructional explanations as well as a sanity check on LLM-based tutoring; to didactics, a new way to look at teaching and lesson-planning at massive scale, by taking a bottom-up approach to modeling the learning and teaching process.

## 2 Background and Related Work

There are many concepts that are common to didactics but are neglected in NLP research. Neither tutoring-related works (Lee et al., 2023; Stasaski et al., 2020) nor concept explanation datasets (Dinan et al., 2019; Jansen et al., 2018) distinguish the type of explanation in social sciences (Miller, 2019) from the interpretation in NLP research.

In science teaching, an explanation is viewed as a practice (or even a purpose) of science or scientists that systematically addresses the questions of "how" and "why" (Kulgemeyer, 2018). Here, **instructional explanations** are those that aim to "communicate a new cognitive model for understanding the world, or how to perform a task, from one understanding-having interlocutor to an understanding lacking one". While most explainability literature has mostly focused on a more philosophical understanding explanation, as that which connects *explanans* and *explanandum* (Miller, 2019), the instructional perspective is closely aligned with the much-needed interest in context for explanations (Mostafazadeh et al., 2020). Despite many systems posing to perform instructional tasks, to our knowledge, they do not take any teaching or learning models into consideration.

**Teaching models** are frameworks to teach teachers how to plan lessons towards better learning outcomes by structuring lessons in accordance with a psychological model of learning. While there have been attempts at unifying multiple teaching and learning models (explaining how learning happens in the mind of the students) (Oser and Baeriswyl, 2002), many remain skeptical about the feasibility (Allensworth et al., 2008). The actual instantiation of them in real-world classroom environments is affected by many socio-cultural elements (Ball and Rowan, 2004), which make it hard to evaluate teaching at scale (Matsumura et al., 2008) and objectively, without considering other teaching activities and social holistic processes surrounding the explanation (Roelle et al., 2015). Boston (2012) abstracted the differences and used broad definitions of the processes, often leading to positive outcomes, but their approach cannot evaluate low-level, dialogical components of the teaching in a classroom. In this paper, we represent teaching processes (1) in the form of teaching acts (Table 1, Table 5) and investigate if language models can capture the distinctions, and (2) as explanation quality measures (Table 6) and an analysis of how well they correlate with expertise levels of the explainee.

**Tutoring datasets** Our work is closest to Wachsmuth and Alshomary (2022): We re-annotate and extend their dataset, perform similar analyses in terms of statistics and LM experiments, but add a new angle to the data with teaching acts and span-level labeling, allowing us to derive quality events in instructional explanations (§5.3) and experiments with LLMs (§5.2). In contrast to CIMA (Stasaski et al., 2020), TSCC-2 (Caines et al., 2022), and NCTE (Demszky and Hill, 2023), their dataset was a good target for modelling different teaching types, as the varied levels also highlight how teaching can change depending on educational level and course subject. Kupor et al. (2023) annotated instruction talk moves in classroom settings and their LMs could perform this classification task well, whereas Macina et al. (2023) and Wang and Demszky (2023) were less successful for applying similar models in neural dialogue tutoring.

**Evaluation of instructional explanations** Previous work in this direction include COH-METRIX, a related suite of measures to assess the quality and readability in discourse automatically (McNamara et al., 2014). Schuff et al. (2023) have also proposed proxy measures for explanation quality based on syntactic and model-based text genera-

| Dialogue acts | Explanation acts | Teaching acts |
|---|---|---|
| **D01**: Check Question<br>Asking a check question | **E01**: Test Understanding<br>Checking whether the listener understood what was being explained | **T01**: Assess Prior Knowledge<br>Checking what the student knows before starting a lesson |
| **D02**: What/How Question<br>Asking a what or a how question | **E02**: Test Prior Knowledge<br>Checking the listener's prior knowledge of the turn's topic | **T02**: Lesson Proposal<br>Proposing the steps that will be taken during the lesson |
| **D03**: Other Question<br>Asking any other question | **E03**: Provide Explanation<br>Explaining any concept or topic to the listener | **T03**: Active Experience<br>Providing the student with puzzle/question to explore; (Student:) Interacting with a mental concept |
| **D04**: Confirming Answer<br>Answering a question with confirmation | **E04**: Request Explanation<br>Requesting any explanation from the listener | **T04**: Reflection<br>Finding gaps in knowledge or inconsistencies; Asking questions about the experience or concept |
| **D05**: Disconfirming Answer<br>Answering a question with disconfirmation | **E05**: Signal Understanding<br>Informing the listener that their last utterance was understood | **T05**: Knowledge Statement<br>Stating the concept(s) being taught via rules or facts |
| **D06**: Other Answer<br>Giving any other answer | **E06**: Signal Non-understanding<br>Informing the listener that the utterance was not understood | **T06**: Comparison<br>Considering similarities and differences between the main concept and other related topics or facts |
| **D07**: Agreeing Statement<br>Conveying agreement on the last utterance of the listener | **E07**: Provide Feedback<br>Responding qualitatively to an utterance by correcting errors | **T07**: Generalization<br>Exploring how the concept applies to new scenarios, experiences and situations outside of the lesson topic |
| **D08**: Disagreeing Statement<br>Conveying disagreement on the last utterance of the listener | **E08**: Provide Assessment<br>Assessing the listener by rephrasing their utterance or giving a hint | **T08**: Test Understanding<br>Finding out if the concept previously established was received correctly and is properly understood |
| **D09**: Informing Statement<br>Providing information with respect to the topic stated in the turn | **E09**: Provide Extraneous Information<br>Giving additional information to foster a complete understanding | **T09**: Engagement Management<br>Maintaining the classroom context to facilitate effective teaching, creating rapport between teacher and student |
| **D10**: Other Act | **E10**: Other Act | **T10**: Other Act |

Table 1: Dialogue, explanation and teaching acts (alongside descriptions) in our ReWIRED dataset.

| # | Topic | Explainer |
|---|---|---|
| 14 | Memory | Daphna Shohamy |
| 15 | Zero-knowledge proofs | Amit Sahai |
| 16 | Black holes | Janna Levin |
| 17 | Quantum computing | Talia Gershon |
| 18 | Quantum sensing | Chandrasekhar Ramanathan |
| 19 | Fractals | Keenan Crane |
| 20 | Internet | Jim Kurose |
| 21 | Moravecs Paradox | Chelsea Finn |
| 22 | Infinity | Emily Riehl |

Table 2: New topics and explainers in ReWIRED on top of the 13 original topics of WIRED which can be found in Wachsmuth and Alshomary (2022).

tion metrics but found low correlation with human judgments. Demszky et al. (2021) develop a framework for measuring teachers' uptake (defined as *building on the student's contribution via, for example, acknowledgement, repetition or elaboration*). Whitehill and LoCasale-Crouch (2024) explore how LLMs can be used to estimate what they define as "instructional support" domain scores with the help of an observation protocol.

## 3 The ReWIRED Dataset

Wachsmuth and Alshomary (2022) classified parts of instructional explanation dialogues from a dataset collected from the 5-levels video series, in which an expert in a topic, such as black holes, or music harmony, explains the topic to people of varying expertise levels:

1. Child,
2. Teenager,
3. Undergraduate college student,
4. Graduate student,
5. Colleague (another expert).

We can see that a great deal of the content actually comprises instructional explanations, especially the lower we go on the educational scale. Wachsmuth and Alshomary (2022) introduced two types of conversational acts and used them to model explanation dynamics between explainer and explainee.

To increase the models' awareness of teaching perspectives, we add a new scheme of teaching acts to their original two dimensions (Table 1 with supplementary examples in Appendix A) and carry out a refined annotation process. We further improve on their work by switching from a turn labelling task (classification) to a span labeling one for greater granularity, leading to better semantic performance. We dub this improved dataset ReWIRED. In the following, we will introduce these teaching acts and our annotation process.

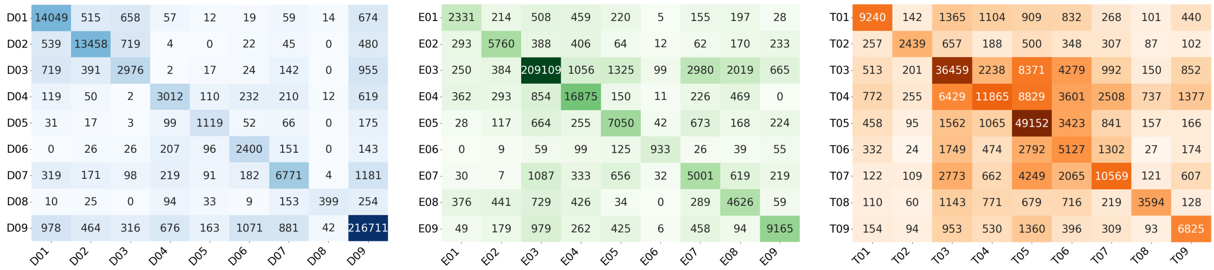


Figure 2: ReWIRED inter-annotator agreements for the three dimensions dialogue (left), explanation (center) and teaching (right) on token level. For better visibility, we have scale-adjusted the colors by `np.log1p(...)`[3]. Each cell shows the number of tokens for which annotators (dis)agreed on a label in a pairwise comparison.

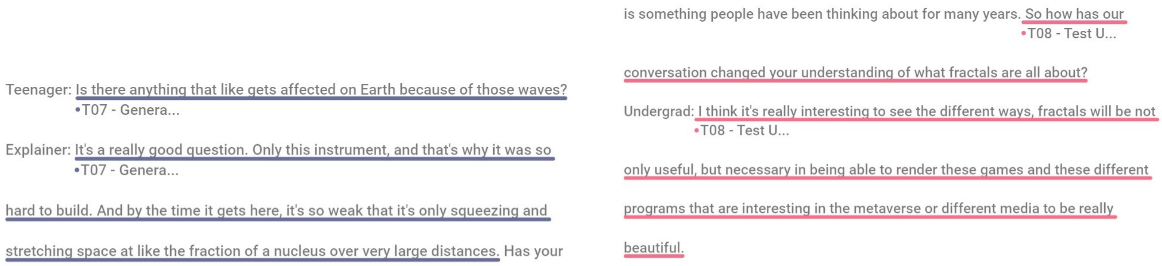


Figure 3: Examples for teaching acts T07 (Generalization) and T08 (Test Understanding).

### 3.1 Teaching acts

Expanding on Wachsmuth and Alshomary (2022), we present a scheme of teaching acts with which to classify dialogues in instructional settings that are coherent with three current and well-accepted teaching models (§2): Teaching as problem solving (**PS**), teaching as concept building (**CB**) (Krabbe et al., 2015), and Oser and Baeriswyl's unified teaching choreographies (**UT**). This is in line with prior work modeling discourse structure in explanations (Bourse and Saint-Dizier, 2012). Concretely, the acts are described in Table 1. Their connection to teaching models and an example[1] are as follows:

- **T01**: *Assess Prior Knowledge* (CB, UT).
- **T02**: *Lesson Proposal* (UT).
- **T03**: *Active Experience* (CB, UT).
- **T04**: *Reflection* (PS).
- **T05**: *Knowledge Statement* (PS).
- **T06**: *Comparison* (UT).
- **T07**: *Generalization* (CB, PS), e.g. Figure 3.
- **T08**: *Test Understanding* (CB), e.g. Figure 3.
- **T09**: *Engagement Management*.
- **T10**: *Other Act*: Any other act that does not fit the above nine acts should instead be placed here.

The main goal of the acts is to bring processes from teaching models closer to the product of their instantiation in actual dialogue (Stolcke et al., 2000), in a way that parts of the dialogue serve as reasonable evidence that the deep processes predicted by teaching models indeed take place.

### 3.2 Annotation

For our annotation task, we asked nine in-house researchers from a (computational) linguistics background to participate in our annotation study. The total of 110 transcripts from 22 topics across five expertise levels (Table 2) were separated into three groups, such that every annotator group annotated the entire dataset exactly once, one third for dialogue acts, one third for explanation acts (using the original act description by Wachsmuth and Alshomary, 2022), and finally one third for our new set of teaching acts. This yielded three sets of annotations for the entire dataset concerning all three acts. This is first to reduce the possibility of bias, as some acts are very similar and annotators might be tempted to just repeat previous annotations; and second to reduce costs. For our annotation platform, we used DOCCANO (Nakayama et al., 2018), which alleviated the span-labeling task. We additionally randomized all conversations to reduce bias further.

Our inter-annotator agreements are at Fleiss' $\kappa = 0.83$ (dialogue acts), 0.79 (explanation acts) and 0.46 (teaching acts). We plot the nine main

[1] Acts with a colored border have an example in both Figure 1 and Figure 8.

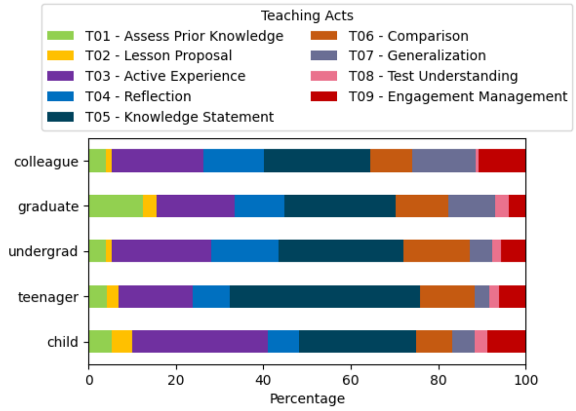


Figure 4: Distribution of teaching acts in ReWIRED across the five expertise levels. Dialogue and explanation act distributions are visualized in Appendix B.

labels of each annotation dimension in Figure 2. They show that there also is quite a bit of uncertainty and confusion regarding our teaching acts because our annotators are knowledgeable in computational linguistics but not so much in pedagogy and didactics. Often confused are E03 and E09, as there is a fine line between what we can deem part of an explanation and what is rather supplementary information, and T06 and T07, since both are about "zooming out" of the topic in question and making a broader set of connections to it. The results of our annotation process are visualized via the distribution of teaching acts in Figure 4.

Our annotation scheme differs from DAMSL (Core and Allen, 1997) and ISO 24617-2 (Bunt et al., 2012) in the granularity of annotations. While there are no dependency relations allowing link structures as in the latter, our annotation scheme enables fine-grained annotation of semantics related to teaching models. Most similar to ours is the CMA schema by Del-Bosque-Trevino et al. (2021) for one-to-one tutorial dialogue sessions: In terms of labels, it vaguely mirrors a lot of acts across all three dimensions, but conflates crucial acts (e.g., *FIM* can be either T02 or T09) and misses out on teaching-related concepts such as Active Experience, Reflection, and Generalization.

## 4 Experiments

To evaluate language models on detecting acts across act dimensions, we conduct two experiments: One on turn-level classification, reproducing Wachsmuth and Alshomary (2022), and one on span-labeling for ReWIRED. For both, we test the hypothesis that fine-tuning a masked LM is more consistent at assigning labels on token-level than LLMs prompted for JSON responses indicating spans and labels.

**Classifying acts** For the turn-level classification of dialogue and explanation acts provided by the original WIRED data, we choose the following baselines: `SVM` with linear kernel for multi-class classification based on `MiniLM` sentence embeddings (Reimers and Gurevych, 2019), and the top-performing `BERT` from Wachsmuth and Alshomary (2022). We compare the following LMs on both tasks: `BERT` for turn-level classification, 110M params; `Stable Beluga 2` (`SB2`) (Mahan et al., 2023; Mukherjee et al., 2023), a type of `Llama-2` model (Touvron et al., 2023), 70B params; `GPT-3.5-turbo-0613`. We provide details on the models in Appendix C.

**Sequence-labeling acts** For the token-level span labeling task of the three annotation dimensions (Table 1) in our new ReWIRED dataset, we analyze the capabilities of the following LMs: As a baseline, a `BERT` for token-level classification with 5-fold cross-validation. We compare it to three prompt-based LLMs: `Stable Beluga 2`; `GPT-3.5-turbo-0613`; `GPT-4-0125-preview`. We provide details on the prompt design for the latter three in Appendix D.

## 5 Results and Discussion

### 5.1 Classifying acts

We show the best performance we were able to attain in automatic act classification for all three acts using several LLMs, and compare our results with the results of Wachsmuth and Alshomary (2022).

Table 3 shows that LLMs perform poorly in turn-level dialogue act classification, except for capturing disagreeing statements and answers (D08, D05). The fine-tuned BERT model outperforms all other approaches by a substantial amount. This is also repeated for the explanation act classification: LLMs only excel in recognizing signals of (non-)understanding. Across all sets of classes, however, we also find that none of the approaches is able to capture the labels with a very low amount of data points (D05, D08, E01, T02; see Tables 4 & 9).

### 5.2 Sequence-labeling acts

Our results for span-level act prediction (Table 4) reveal that this task is very challenging for the LLMs, since they were not fine-tuned on the task.

| Dialogue acts | D01 | D02 | D03 | D04 | D05 | D06 | D07 | D08 | D09 | D10 | Macro-$F_1$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| W&A BERT-seq | 76.00 % | 72.00 % | 0.00 % | **35.00** % | 67.00 % | 0.00 % | 69.00 % | 0.00 % | 87.00 % | 61.00 % | 47.00 % |
| SVM + SentTf | 64.30 % | 59.55 % | 0.00 % | 7.14 % | 86.96 % | **7.69** % | 76.28 % | 0.00 % | 83.30 % | 68.57 % | 68.71 % |
| BERT | **87.35** % | **82.81** % | 0.00 % | 0.00 % | 80.77 % | 0.00 % | **82.04** % | 0.00 % | **94.62** % | **76.77** % | **81.67** % |
| SB2 | 20.00 % | 41.51 % | 0.00 % | 14.29 % | **100.00** % | 0.00 % | 28.57 % | 0.00 % | 78.67 % | 0.00 % | 31.45 % |
| GPT-3.5 | 14.33 % | 43.36 % | **4.41** % | 19.15 % | 37.93 % | 5.92 % | 21.41 % | **8.00** % | 69.51 % | 33.88 % | 25.79 % |
| **Expl. acts** | **E01** | **E02** | **E03** | **E04** | **E05** | **E06** | **E07** | **E08** | **E09** | **E10** | **Macro-$F_1$** |
| W&A BERT-seq | **27.00** % | 64.00 % | 84.00 % | 64.00 % | 33.00 % | 21.00 % | 60.00 % | **15.00** % | 8.00 % | 56.00 % | 43.00 % |
| SVM + SentTf | 6.90 % | 66.34 % | 81.37 % | 37.89 % | 13.84 % | 0.00 % | 72.99 % | 0.00 % | **28.07** % | 55.81 % | 63.23 % |
| BERT | 0.00 % | **73.05** % | **93.71** % | **78.26** % | 5.52 % | 0.00 % | **74.89** % | 0.00 % | 0.00 % | **66.04** % | **66.67** % |
| SB2 | 13.79 % | 46.60 % | 81.63 % | 48.89 % | **43.53** % | 18.18 % | 15.13 % | 0.00 % | 9.68 % | 0.00 % | 27.74 % |
| GPT-3.5 | 16.87 % | 38.76 % | 71.70 % | 23.30 % | 37.00 % | **28.30** % | 5.06 % | 0.00 % | 2.86 % | 27.85 % | 27.17 % |

Table 3: Language models evaluated on the tasks of classifying dialogue and explanation acts of whole dialogue turns from the WIRED dataset. We use the previous metrics (W&A BERT-seq) found by Wachsmuth and Alshomary (2022) as our baseline. Percentages under each of the acts show micro-$F_1$ scores.

| Dialogue acts | D01 | D02 | D03 | D04 | D05 | D06 | D07 | D08 | D09 | Macro-$F_1$ | Span Al. |
|---|---|---|---|---|---|---|---|---|---|---|---|
| BERT | **73.14** % | **72.72** % | **74.02** % | **55.43** % | **50.25** % | **66.28** % | **60.59** % | **43.14** % | **94.86** % | **69.01** % | – |
| SB2 | 21.66 % | 54.27 % | 2.83 % | 7.63 % | 39.16 % | 9.03 % | 33.66 % | 22.78 % | 93.50 % | 28.72 % | 59.61 % |
| GPT-3.5 | 19.71 % | 54.73 % | 11.69 % | 0.00 % | 8.70 % | 7.01 % | 19.74 % | 12.98 % | 83.87 % | 22.30 % | 59.41 % |
| GPT-4 | 34.25 % | 57.44 % | 2.38 % | 14.32 % | 27.13 % | 9.42 % | 34.71 % | 28.97 % | 93.12 % | 31.45 % | **63.18** % |
| **Expl. acts** | **E01** | **E02** | **E03** | **E04** | **E05** | **E06** | **E07** | **E08** | **E09** | **Macro-$F_1$** | **Span Al.** |
| BERT | **64.66** % | **67.21** % | **94.69** % | **72.81** % | **64.80** % | **69.09** % | **64.99** % | **80.65** % | **80.34** % | **75.89** % | – |
| SB2 | 8.93 % | 33.63 % | 89.08 % | 56.00 % | 31.67 % | 17.97 % | 20.21 % | 0.00 % | 4.64 % | 26.22 % | 60.54 % |
| GPT-3.5 | 20.06 % | 10.02 % | 84.27 % | 24.23 % | 16.90 % | 19.35 % | 4.69 % | 0.00 % | 7.07 % | 18.66 % | 49.72 % |
| GPT-4 | 27.70 % | 42.11 % | 86.18 % | 66.52 % | 34.82 % | 42.93 % | 19.94 % | 9.07 % | 20.77 % | 35.00 % | **61.49** % |
| **Teaching acts** | **T01** | **T02** | **T03** | **T04** | **T05** | **T06** | **T07** | **T08** | **T09** | **Macro-$F_1$** | **Span Al.** |
| BERT | **81.57** % | **62.38** % | **85.00** % | **80.85** % | **89.61** % | **86.34** % | **85.67** % | **79.57** % | **72.91** % | **82.36** % | – |
| SB2 | 28.24 % | 28.04 % | 13.23 % | 8.42 % | 49.12 % | 7.83 % | 2.09 % | 10.21 % | 29.44 % | 19.62 % | **44.39** % |
| GPT-3.5 | 22.89 % | 8.95 % | 19.10 % | 7.25 % | 40.31 % | 10.31 % | 11.80 % | 5.13 % | 13.66 % | 15.49 % | 31.55 % |
| GPT-4 | 31.21 % | 26.32 % | 16.80 % | 5.58 % | 47.23 % | 14.71 % | 16.02 % | 10.93 % | 25.63 % | 21.60 % | 39.55 % |

Table 4: Language models evaluated on the tasks of sequence-labeling dialogue, explanation and teaching acts within dialogue turns from our ReWIRED dataset. Percentages under each of the acts show micro-$F_1$ scores. Act 10 was disregarded due to low number of instances, close-to-zero scores and irrelevance for the overall performance.

Still, they can handle the majority classes reasonably well (D02, E04, T05) or very well (D09, E03). However, in all other cases, all LLMs fail to assign the correct label consistently enough. Between the models, GPT-4 has a slight edge over SB2, which in turn is a lot more accurate than GPT-3.5. The difference in model performance is more pronounced for the already established acts (dialogue, explanation), but less so for our new teaching acts, whose label taxonomy is unlikely part of their training data. Evaluating how well the extracted spans align with human-annotated spans (rightmost column) reveals a similar pattern, i.e. GPT-4 beating the rest, except SB2 coming out on top for the teaching acts.

The prompt design that elicits structured prediction in the form of JSON objects from LLMs causes major problems for post-processing. After rigorously handling edge cases, we still find that 12.82 % of SB2, 9.73% of GPT-3.5 and 3.18 % of GPT-4 outputs result in invalid, unparseable JSONs. While the first two models repeatedly predicted duplicate spans with the same labels, in rare cases with an alternative label, GPT-4 tends to continue with a rationale explaining the annotation. These findings reflect challenges reported by concurrent related work applying LLMs to dialogue-related tasks (Zhao et al., 2023) and span-labeling tasks (Ziems et al., 2024; Wang et al., 2023) and the general difficulty of applying them to teaching settings (Wang and Demszky, 2023; Macina et al., 2023).

BERT, on the other hand, easily outperformed the prompt-based LLMs across every single act. The stark difference can be attributed to the importance of fine-tuning and the constraint to predict one of the ten acts. For span-labeling tasks like this, especially in the teaching act dimension where the performance is the overall highest, we recommend practitioners to look into such a controlled setup instead of unreliable prompt designs.

### 5.3 Quality Events in Instructional Explanations

Based on our annotation schema and as an additional analysis, we develop and propose a test suite based on didactics research. This novel assessment framework, which is termed as IXQUISITE,

| Category | Description | Origin | Measure |
|---|---|---|---|
| Check for prior knowledge | The teacher inquires the student about prior knowledge, background, or what their interests might be | Kulgemeyer and Schecker (2009), Leinhardt and Steele (2005) | T01 |
| Mindfulness of common misconceptions | The teacher addresses common misconceptions | Wittwer et al. (2010), Andrews et al. (2011) | T04 |
| Rule-Example structure | The teacher states the abstract form of the concept being taught. Then the teacher gives some example to assist understanding | Tomlinson and Hunt (1971) | T05 $\rightarrow$ T03 |
| Example-Rule structure | For procedural knowledge, the teacher first provides examples and then derives the general rule from them | Champagne et al. (1982) | T03 $\rightarrow$ T05 |
| Example/Analogy connection | The teacher explains how parts of the analogy/example relate to the concept being explored | Ogborn et al. (1996), Valle and Callanan (2006) | T06 |
| Check for understanding | The teacher tests the understanding of the student | Webb et al. (1995) | T08; E01 |
| Remedial explanations | Either the teacher praises correct understanding (positive reinforcement) or corrects improper understanding | Roelle et al. (2014), Sánchez et al. (2009) | E08 |

Table 5: Explanation and teaching acts-related measures in IXQUISITE for instructional explanation quality based on occurrences of classes from our annotation schema.

| Category | Description | Origin | Measure |
|---|---|---|---|
| Minimal explanations | Low cognitive load, e.g. avoid redundancies (verbosity) such as introducing named entities | Black et al. (1986) | Frequency of named entities |
| Lexical complexity | The level of difficulty associated with any given word form by a particular individual or group | Kim et al. (2016) | Frequency of difficult words |
| Synonym density | Children are proven better aligned with consistent terminology; experts allow more synonyms | Wittwer and Ihme (2014) | Frequency of synonyms for the $n$ terms most connected to the topic |
| Correlation to teaching model | Correlation of teaching act order to prescribed teaching models | Oser and Baeriswyl (2002), Krabbe et al. (2015) | Edit distance between T01-T08 (asc.) and actual occurrences |
| Adaptation | The teacher incorporates prior knowledge, misconceptions and interests and uses analogies | Wittwer et al. (2010) | Inverse frequency of synonyms in the text |
| Readability level | Indicator of how difficult a passage is to understand | Crossley et al. (2017) | Flesch-Kincaid Grade level |
| Coherence | How sentences relate to each other to create a logical and meaningful flow for the reader or listener | Lehman and Schraw (2002), Duffy et al. (1986) | Frequency of conjunctions and linking language |

Table 6: Categories for instructional explanation quality and associated numerical measures in IXQUISITE.

addresses both the *form* of instructional explanations (in terms of syntax, vocabulary, etc) and their *function* (as present in the form of different classes in our annotation). While we only carry out analyses on and evaluate the ReWIRED dataset, we are confident that IXQUISITE can be applied to other kinds of instructional explanations, both human- and LLM-generated, among others.

**The IXQUISITE test suite** Since teaching models propose themselves as a proper method for instantiating learning, evaluating teaching according to their adherence to the prescribed method is also natural. We find that teaching models can serve as a quality metric and an opportunity to operationalize many other proposed evaluation metrics from didactics. We provide a new way to interact with the problem by providing a suite of tools that measure quality based on a large selection of proposed quality features from didactics literature. Through our suite of low-level quality tests, we aim to verify didactics theory in a controlled environment at a relatively low cost (using existing libraries, e.g., NLTK, SPACY, and TEXTSTAT). Following the literature review by Kulgemeyer (2018), we were able to track a list of seven events, which, when detected, have been shown to correlate to better learning outcomes, and seven more numerical metrics, which are the discrete values resulting from properties associated with better learning outcome. The events and metrics, along with their descriptions, are listed in Table 5 and Table 6, respectively.

**IXQUISITE results** The qualitative act-based measures, as well as the metrics correlate well with the expert levels present in the ReWIRED dataset, as seen in Figure 5. In terms of the former, testing for understanding and remedial explanations

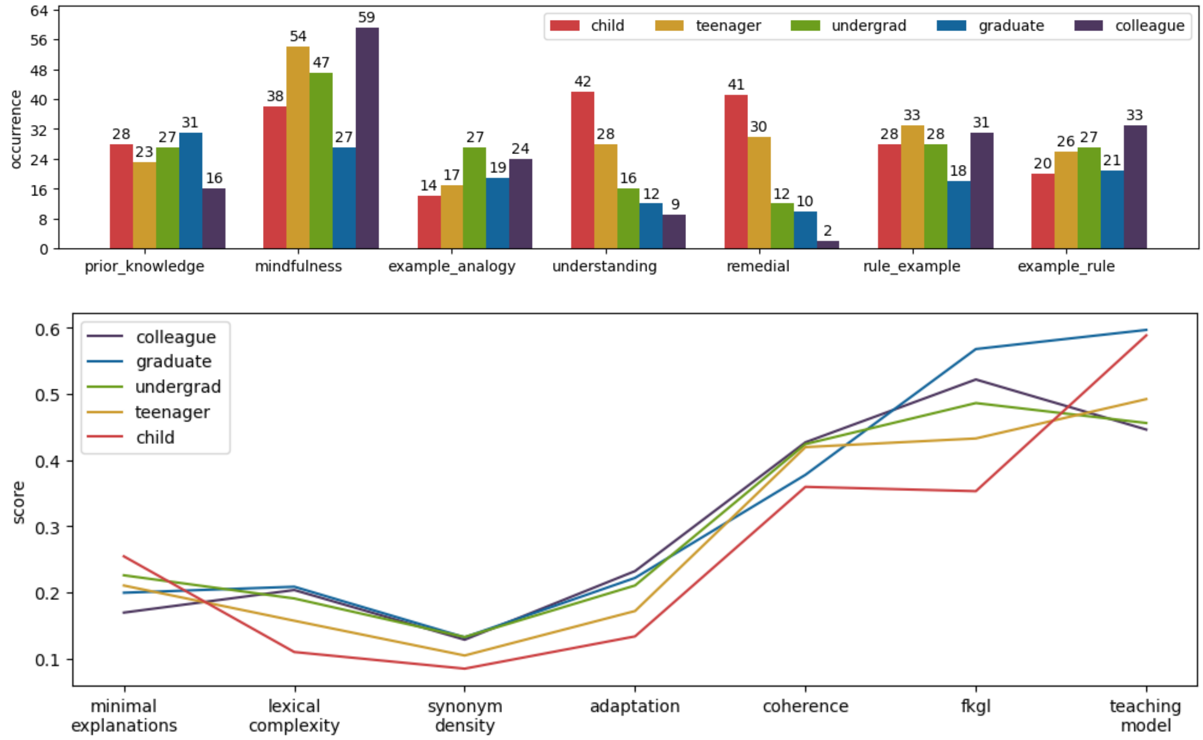


Figure 5: IXQUISITE results with scores from explanation and teaching act-related measures (Table 5; top) and for the five levels in ReWIRED by category according to Table 6 (bottom).

are mostly present in lower expertise levels, which is expected. *Mindfulness (of common misconceptions)* is especially high for colleague-level explanations and reflects the variation in conversation topics present in the dataset. It is also interesting to note that both *rule-example* and *example-rule* structures are exceptionally present as well as in teenager- and colleague-addressed dialogues.

Regarding our numerical metrics, we observe that explanations tailored to a child present a lower bound across all our metrics, including a lower lexical complexity, reading grade, synonym density, and coherence. However, a general trend is that graduate-level explanations score higher than colleague-grade explanations (e.g., teaching model correlation), probably because they are more focused towards the actual topic of discussion, while colleague-grade dialogues might also contain chitchat and other topics, thus not necessarily following a teaching-like approach. In the case of adaptation, graduate-level explanations are an outlier, where the score is lower, which is a surprising result. Lastly, minimal explanations' scores for children average higher, possibly because of an attempt to establish a common ground with world knowledge via entities.

## 6 Conclusion

We presented an extended dataset of instructional explanation dialogues in one-to-one tutorial sessions, ReWIRED, adding span-level annotations and new teaching acts dimension reflecting good practices according to didactics. Our language model analyses on the span-labeling tasks show that LLMs, including GPT-4, fall far behind controlled setups like a fine-tuned BERT in reliably detecting acts across multiple act dimensions. Our IXQUISITE suite of metrics for quality events in instructional explanations represent the different expertise levels of explainees well and are a first step in operationalizing pedagogical psychological theory for tutorial dialogues in NLP.

In the future, we plan to follow concurrent work in exploring LLM-based explanation quality evaluation (Rooein et al., 2023), especially for metrics such as Adaptation and Mindfulness of common misconceptions. These are hard to capture with the more traditional approach we chose and instead require world knowledge that LLMs can provide. Further data collection and fine-tuning will also allow mimicking the behavior found in classroom transcripts for multi-turn systems. This forms a fertile basis for more satisfactory explanation dialogues from automated tutoring systems.

## Limitations

Resulting from the low inter-annotator agreement for the teaching acts as discussed in §3.2, we want to perform data collection involving teachers and didacticians in the future. Additionally, a portion of our test suite relies on human annotation, a factor that may introduce inconsistencies. In this case, replication or extension of the test suite might be difficult without a reliable teaching act prediction model.

Due to time and budget constraints, we were not able to explore many different prompt patterns in our LLM experiments. The prompt design utilized in our study may not represent an ideal formulation, potentially influencing the model's performance.

The dataset we present is extracted from videos - in the transcription, audio and visual elements are not present. The efficacy of our approach may vary depending on the complexity and diversity of the multimodal inputs, if present.

Last but not least, the generalizability of our findings may be constrained by the narrow domain of dialogues examined, limiting extrapolation to broader conversational contexts.

## Ethical statement

We do not see any immediate ethical concerns with respect to research and development. The data included in the corpus is readily available from the WIRED web resources. The nine annotators in our study were paid the minimum wage in conformance with the standards of our host institutions' regions. In our view, the provided prediction models target dimensions of dialogue turns that are not prone to be misused for ethically doubtful applications.

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# Appendix

## A Examples for acts

Figures 6, 7, and 8 show examples from ReWIRED for each of the acts as provided to the annotators.

## B Label distributions

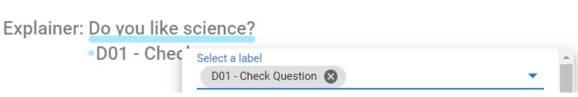
Figure 9 shows the distribution of annotated acts in the dialogue and explanation dimensions.

## C Models

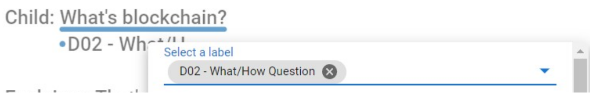
- `MiniLM` sentence embeddings: https://huggingface.co/sentence-transformers/all-MiniLM-L6-v2
- `BERT`: https://huggingface.co/bert-base-uncased
- `Stable Beluga 2`: https://huggingface.co/petals-team/StableBeluga2
- `GPT-3.5` and `GPT-4`: https://platform.openai.com/docs/api-reference/chat

## D Prompt design

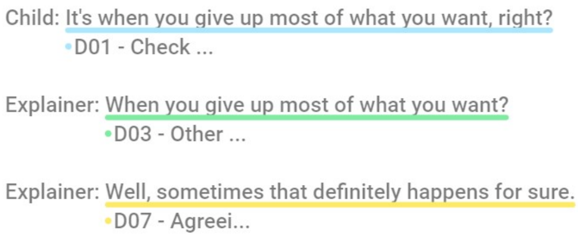
Figure 10 and Figure 11 depict the prompts used with `SB2`, `GPT-3.5` and `GPT-4` to produce the predictions whose evaluation is shown in Table 3 and Table 4, respectively.



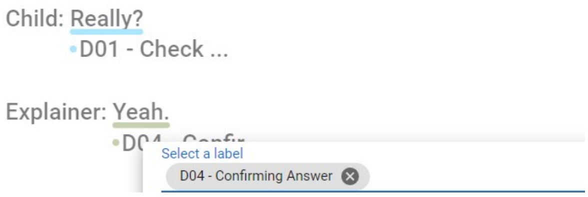

(a) D01: Check Question



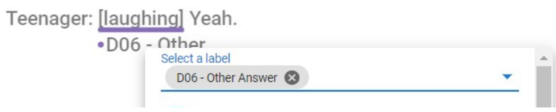

(b) D02: What/How Question



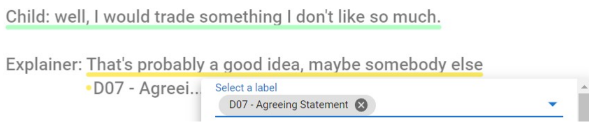

(c) D03: Other Question



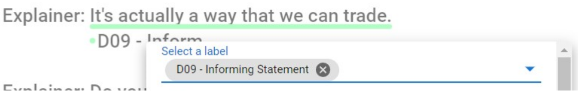

(d) D04: Confirming Answer



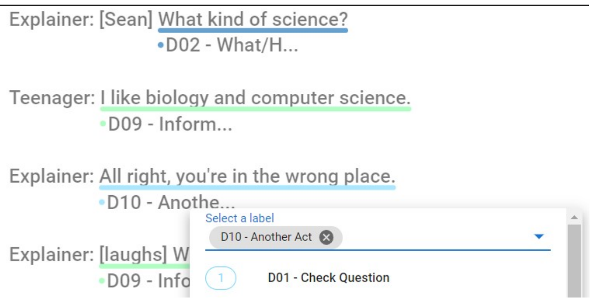

(e) D06: Other Answer




(f) D07: Agreeing Statement

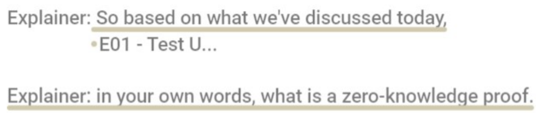



(g) D09: Informing Statement

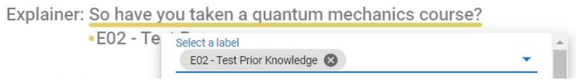



(h) D10: Other Act

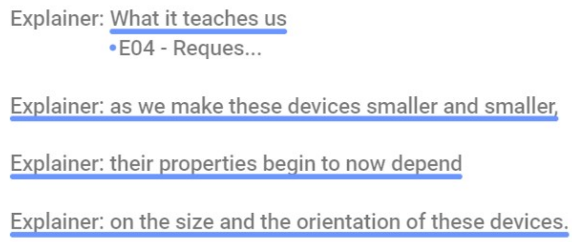
Figure 6: Examples for dialogue acts. D05 and D08 are left out, because they are analogous to D04 and D07, respectively.




(a) E01: Test Understanding

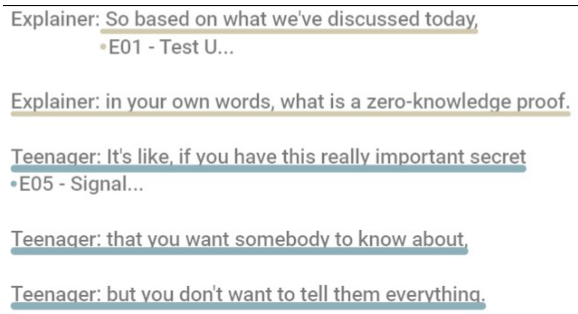



(b) E02: Test Prior Knowledge

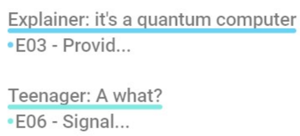



(c) E03: Provide Explanation (The color/label is wrong here!)

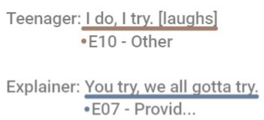

(d) E04: Request Explanation



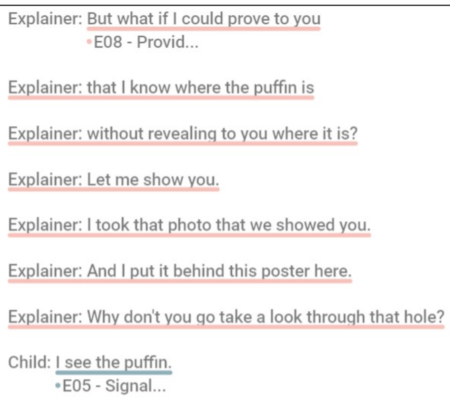

(e) E05: Signal Understanding



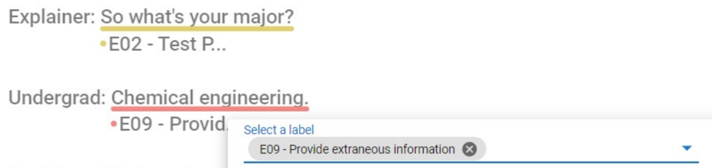

(f) E06: Signal Non-understanding



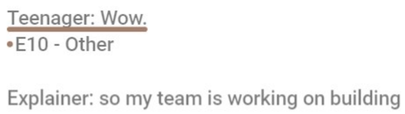

(g) E07: Provide Feedback




(h) E08: Provide Assessment

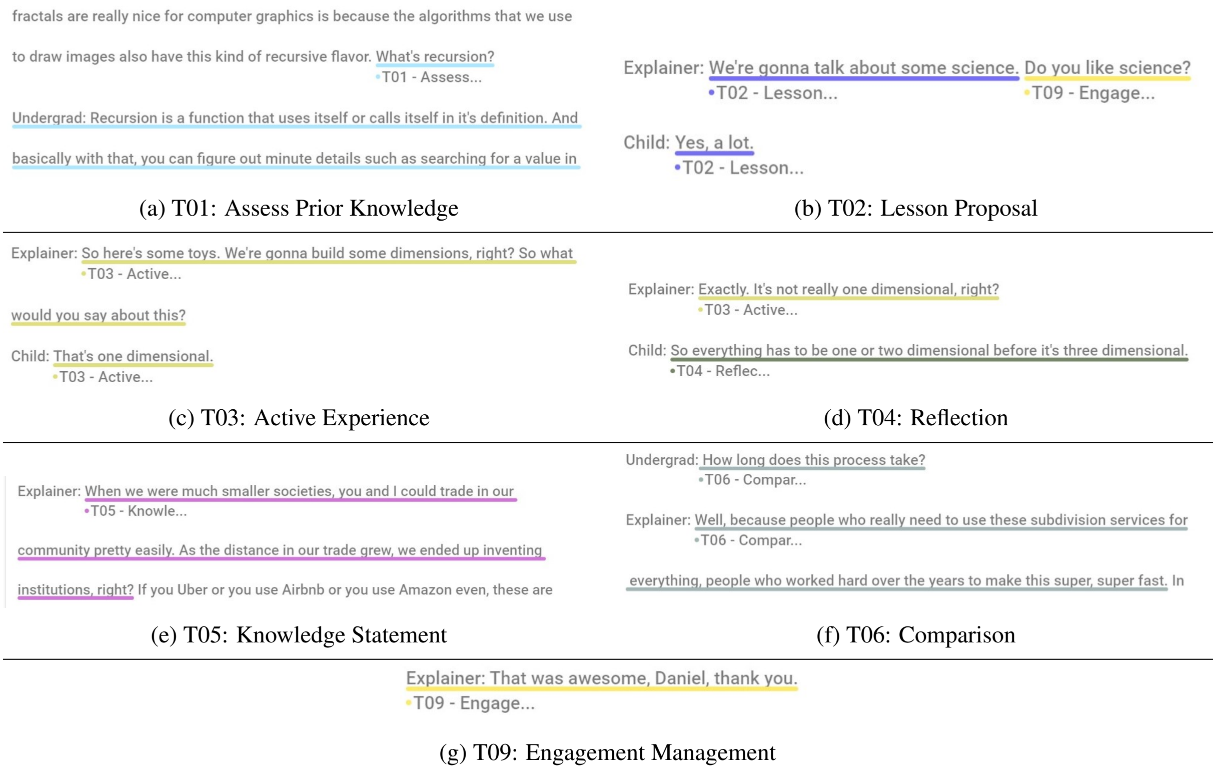



(i) E09: Provide Extraneous Information




(j) E10: Other Act

Figure 7: Examples for Explanation Acts.



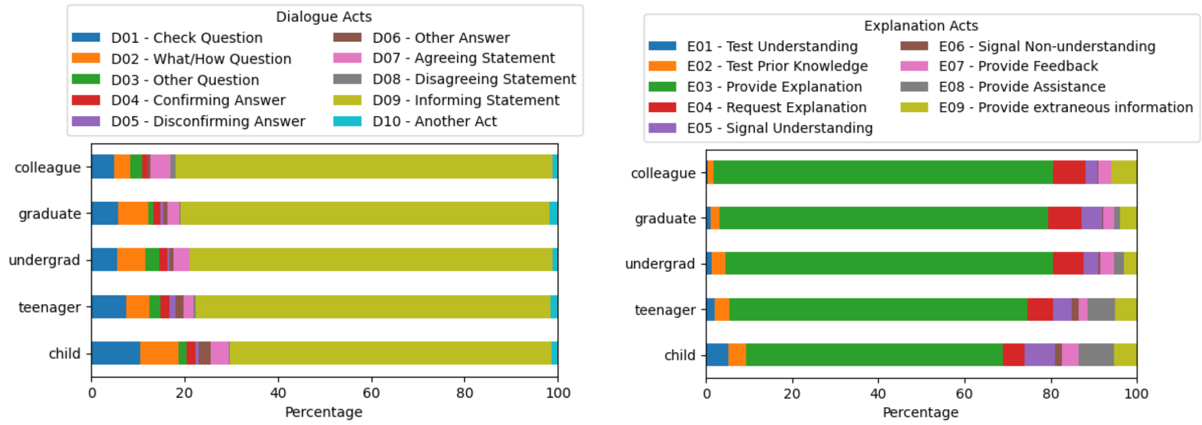

(a) T01: Assess Prior Knowledge (b) T02: Lesson Proposal

(c) T03: Active Experience (d) T04: Reflection

(e) T05: Knowledge Statement (f) T06: Comparison

(g) T09: Engagement Management

Figure 8: Examples for teaching acts T01-T06 and T09. Examples for T07 and T08 are in Figure 3.




(a) Distribution of dialogue acts (b) Distribution of explanation acts

Figure 9: Distribution of annotated acts in ReWIRED across the five expertise levels for three dimensions dialogue (a) and explanation (b).

```python
system_prompt = (f"You are an expert annotator. In the following, you will be requested to classify a single turn of a dialogue between explainer and {student_role}.\n")
# Example label mapping (dialogue acts)
WIRED_da_label_mapping = {
    '(D01) To ask a check question': 1,
    '(D02) To ask what/how question': 2,
    '(D03) To ask other kind of questions': 3,
    '(D04) To answer a question by confirming': 4,
    '(D05) To answer a question by disconfirming': 5,
    '(D06) To answer - Other': 6,
    '(D07) To provide agreement statement': 7,
    '(D08) To provide disagreement statement': 8,
    '(D09) To provide informing statement': 9,
    '(D10) Other': 10,
}
label_schema = ("The label schema consists of the following 10 classes:\n* " + "\n* ".join(list(WIRED_da_label_mapping.keys())) + "\n")
read_instruction = f"The excerpt from the dialogue:\n{turn_text}\n"
task_instruction = "Predicted label:\n"
# Combine inputs to single string
entire_prompt = system_prompt + label_schema + read_instruction + task_instruction
```

Figure 10: Simplified version of the Python code showing the turn classification task prompt for WIRED.

```python
system_prompt = (f"You are an expert annotator. ")
read_instruction = (f"Here is one turn from a dialogue between an explainer and a {student_role} on the topic of {topic}:\n{turn_text}\n")
task_instruction = ("Please extract the spans from the turn and assign a label to each of the spans. It is possible that the whole turn is just one span, because the act applies to its entirety. Please present your predictions in a JSON format like this: {\n\t{\n\t\t'Span': '...', \n\t\t'Predicted label': '...' \n\t},\n}\n")
entire_input = system_prompt + read_instruction + label_schema + task_instruction
```

Figure 11: Simplified version of the Python code showing the span labeling task prompt for ReWIRED.